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INTELLIGENCE ANALYSIS OF EMPIRICAL DATA BASED ON TIME SERIES

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ABSTRACT

Context. The problem of intelligent data analysis for assessing the stability of operators' functioning as a component of safety management is considered.The object of the study was to verify estimates of the complexity and chaotic nature of physiological processes based on nonlinear dynamics methods.

Objective. The goal of work is intelligent data analysis for assessing the stability of the functioning of a dynamic system based on the methods of non-linear dynamics.

Method. Data intelligence to obtain additional useful information to avoid wrong decisions when deciding on the current state of the operator to be able to perform professional duties. Quantitative assessment of the complexity of physiological dynamics to determine the stability of feedback control processes of body subsystems and their constant adaptation to changes in environmental conditions. The presence of significant nonlinearities in the biomedical signals of the body is associated with the appearance of a chaotic component that describes the chaotic nature of the body's processes. Due to the fact that biomedical signals have both a periodic and a chaotic component, the study of the latter makes it possible to determine the informational component of the nature of the internal organization of the organism and provide information about the possible destabilization of the functional state of the operator. The use of nonlinear dynamics methods to study changes in the operator's body and provide additional independent prognostic information complementing traditional data analysis in the time and frequency domains. Several indices obtained by the methods of nonlinear dynamics are proposed, which contribute to the expansion of the diagnostic solution based on the available data.

Results. The results of the study can be used during the construction of mathematical methods of non-linear dynamics to describe empirical data of this kind.

Conclusions. Experimental studies have suggested recommending the use of non-linear methods dynamics as an an additional independent component that allows analyzing the chaotic component of biomedical signals to avoid wrong decisions during professional selection and assessment of the current state of aviation industry operators as one of the causes of adverse events in aviation. Prospects for further research may include the creation of a methodology based on nonlinear dynamics methods that will allow to increase the reliability of predicting a malfunction of the cardiovascular system as an indicator of a change in the balance of the functional state of the operator based on additional informative parameters, which can be used to assess triggers that may cause an adverse event in aviation, as well as an experimental study of the proposed mathematical approaches for a wide range of diagnostic problems.

KEYWORDS: methods of non-linear dynamics, entropy, MATLAB, RR-interval, operator, Hausdorff dimension, highest Lyapunov exponent, attractor.

ABBREVIATIONS

ApEn is an Approximate Entropy;
ECG is an Electrocardiograms;
EEG is an Electroencephalograms;
HRV is a Heart rate variability;
LF is a Low Frequency;
NLD is a Nonlinear dynamics;
SampEn is a Sample Entropy;
SD is a Standard Deviation;
SRM is a Safety risk management;
SRP is a Safety risk portfolio.

NOMENCLATURE

v is a vector function of given smoothness r;
M is phase space of system;
R^n is an area of some set;
$F^t(x)$ is a smooth function defined for values t;
Ω is the Poincare mapping;
Ψ is a global secant the flow F^t;
E is a secant surface that the cycle intersects at the point p;
U is a neighborhood of a compact subset A;
A is a compact subset of the phase space M;
$N(\delta)$ is a number of cells of size δ covering the curve;
λ is a highest Lyapunov exponent;
H_D is a Hausdorff dimension;
$\delta(t)$ is a distance between two states of the system;
$x(t)$ is a time series;
x is a realization of all observations;
$x(i)$ is an all readings of x realization;
ε is a near trajectories;
τ is a time interval after the start of the comparison;
$S(t)$ is a steepness of the curve on the linear section which determines the Lyapunov exponent λ;

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R is an absolute range function;
$B_H(t)$ is a fractal Gaussian function;
S is a positive constant;
t_1, t_2 are counts at time points 1 and 2;
$\xi(t)$ is an existing time series;
$\langle \xi(t) \rangle$ is an average value.

INTRODUCTION

The results of the analysis of the flight safety risk portfolio (Safety risk portfolio – (SRP)), for the period from 2016 to 2020, and the results of statistical and analytical processing of flight safety data using the web portal https://rmd.avia.gov.ua/ determine the connection between heart diseases as flight safety problems and key areas of risk in aviation and demonstrate their contrbution to the occurrence relevant (potential) dangerous consequences in aviation. In addition, the analysis of the current functional state based on the biomedical signals of the heart (electrocardiogram, heart rate, heart rate variability) allows to make a decision regarding the stability of the balance of the entire body of the aviation operator and, as a result, to determine the probability of erroneous decisions in the professional field. That is, to determine the accompanying factors that can cause aviation events. Therefore, extracting reliable information about the state of the cardiovascular system as an indicator of stability (homeostasis) of the operator's entire body is an urgent task for the intellectual analysis of biomedical data.

The object of study is the process of analysis of heart rate variability (HRV) by methods of non-linear dynamics to improve the reliability of the assessment of the nature of the activity of all systems of the body.

The analysis of complex HRV signals leads to the need to quantify the complexity of physiological dynamics using various indicators that take into account nonlinearity, time irreversibility, fractality and long-term correlations.

The subject of study is the process of evaluation of additional information indicators, what is taken by methods of non-linear dynamics that can be used to predict changes in the functional state of the operator as one of the triggers of an adverse event in the safety risk management (SRM) of aviation.

For this reason, the main task of the study is the analysis of stability, the study of the role of invariant manifolds, the analysis of the geometric structure of trajectories of attractors, the search for invariant measures, and the calculation of invariant characteristics. Although this approach does not make it possible to represent the solution in an explicit form, it allows us to qualitatively describe many important features of the cardiovascular system as an indicator of the dynamism of the whole organism, including randomness.

Due to the variability, unpredictability and instability of the object from which the information indicators are obtained, there are many factors influencing the reliability decision-making about the functional state of the operator's body and can lead to incorrect conclusions and false extrapolations. This is due to the fact that such information indicators have structural features and therefore cannot be adequately described by standard m-ethods, because different subsystems of the body as control loops operate in a complex relationship with feedback for constant adaptation of the entire system to changing external influences. The subject of the study is the process analysis HRV by methods non-linear dynamics with non-standard approaches to the data quantification of empirical data.

Intelligent data analysis involves obtaining reliable information about a complex system with stochastic influence. Such a complex system is the organism of the operator, which is under the influence of external destabilizing factors when performing his professional duties. Empirical data obtained from a biological object, on the basis of which such an analysis can be carried out, possible presented using time series [1].

Such a presentation allows, in addition to quantitative values of medical and biological parameters, to obtain additional information about dynamic changes in the state of the system at different time intervals. Moreover, the time during which these empirical data were obtained also has an informational component. Most medical and biological parameters such as ECG, electromyograms, HRV, EEG characterize both linear physiological processes and have a component that describes certain non-linear processes in the body as the body's reaction to external destabilizing influences. While the linear component of the system, with a certain reliability, is described by classic methods of intellectual analysis, nonlinear processes in the body are described and investigated insufficiently [1, 2].

The purpose of the work is to increase the hang the reliability of the use of mathematical methods to describe the functional state change of the operator using transformation information indicator in decision-making system.

1 PROBLEM STATEMENT

At present, to study the properties of complex systems, including in experimental studies, the approach is widely used, based on the analysis of the signals generated by the system. This is especially relevant in cases where it is practically impossible to describe the process under study mathematically, but researchers have at their disposal is some characteristic observable quantity. Analysis of this approach constitutes the content of this article.

Therefore, in the presented work, as an example, the formalization of the theory of chaotic dynamic systems for the analysis of the stability of the functional state of a biological object is presented.

Since the time of A. Poincaré, it has become clear that when studying complex behavior, the usual approach such as analytical calculations of individual trajectories of differential equations does not work. For this reason, the main task of the theory is the study of stability, the study

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of the role of invariant manifolds, the analysis of the geometric trajectory structures, search for invariant measures, calculation of invariant characteristics, etc. Although this approach does not make it possible to represent the solution in an explicit form, it allows us to qualitatively describe many important features of dynamical systems, including randomness. If there is a set of ordinary differential equations:

$$\dot{x} = \upsilon(x, a),$$

where $x(t) = \{x_1, x_2, ..., x_n\}$ – set of dynamic variables, t is time, $v = \{v_1, v_2, ..., v_n\}$ is a vector function of given smoothness r (that is, of class C^r) defined in some domain $M \subseteq R^n$, v: $M \to R^n$, a is some parameter (or their combination) and M is phase space of system (1).

The function v generates a flow $F^t : M \to R^n$, where $F^t(x)$ is a smooth function defined for values t from the interval $T \subseteq R$, such that for all $x \in M$ and $\tau \in T$:

$$\frac{d}{dt} F^t \Big|_{t=\tau} = \upsilon(F^t(x)).$$

The flow F^t is sometimes called a shift transformation because it takes the system from the state it was in at the initial time to the state at any other time. It is easy to understand that F^s with $s=-t$ has an inverse function of the same smoothness C^r, i.e. the system is time reversible.

Geometrically, the system of equations (1) can be interpreted as a vector field that associates each point $x \in M$ with the vector v. Then the solution $x(t) = F^t(x(0))$ is a certain curve, which at every point is tangent to this vector field. If the initial state $x(0) = x_0 \in D$ is given system (1), then $F^t(x_0)$:$T \to R^n$ defines the phase trajectory or phase curve of the original differential equation (1). In some cases, the flow F^t admits a global secant Ω, i.e. a hypersurface of dimension $n-1$, which the phase trajectories intersect transversally. Then the study of the behavior of the original system can be reduced to the analysis of the mapping Ω:Ψ→Ψ, which is the Poincare mapping.

When analyzing dynamical systems, it is also necessary to take into account limit cycles-closed phase trajectories corresponding to the periodic behavior of the system. If $\gamma = x(t)$ is a limit cycle and E is a secant surface that the cycle intersects at the point p. The attractor as a compact subset A of the phase space M satisfies the following conditions: A is invariant with respect to the flow of the dynamical system; there is a neighborhood U that shrinks to A under the action of the flow. If we choose some neighborhood $U \subset E$ of this point and consider the first return of the trajectory that left the point $q \in U$ close to p. Then we can define the Poincaré map Ω: $U \to E$ that sends the point q to the point $q' = \varphi(q)$ on the surface E.

The main property of dissipative systems is the compression of the phase volume: over time, according to the dynamic equation, the initial volume occupied by the cloud of phase points decreases. Formally, this is expressed as the inequality div $v < 0$. In this case, as $t \to \infty$, all phase trajectories will converge to some subset $A \subset M$ of zero (in phase space) volume, which is an attractor of a dynamical system and makes it possible to estimate the stability of its behavior. That is, for a given selection x, it is necessary to construct an attractor of a dynamic system and, simultaneously with the analysis of a cloud of phase points, obtain quantitative characteristics using methods of nonlinear dynamics to confirm the conclusions about the stability of the system.

2 REVIEW OF THE LITERATURE

The nonlinear phenomenon is one of the reasons for the variability of medical and biological parameters, the HRV in particular [3]. If the studies of the twentieth century were devoted to the description of a biological system as a linear one for which a pathological process can be determined with a certain reliability due to comparison with the generally accepted norm – the approach of normology [4, 5]. Thus, employees of the Kyiv Research Institute of Medical Problems of Physical Culture and Sports of the Ministry of Health of Ukraine (1968–1986) worked fruitfully in the direction of studying the state of the body of a practically healthy person, forming a scientific school that is actively working today [6, 7].

At the beginning of the twenty-first century, more and more studies prove the need to study the nonlinear component of biological processes [8, 9] to obtain, firstly, additional information about the transformation of biological processes due to reverse biological connections, to ensure the balance of functioning of the organism [10]. Secondly, they provide information about a sufficient number of internal resources to ensure physiological balance under the influence of destabilizing factors [11, 12]. Thirdly, it is a valuable tool for analyzing the medical and biological indicators of population groups that have already undergone professional selection and their medical and biological parameters are within the normal range, but professional destabilizing factors can deplete the resources available in the body, and for their effective use, non-standard approaches to assessment are required the level of regulation of the stability of the organism's functioning, taking into account their chaotic nature [13, 14].

In the paper, processing by methods of non-linear dynamics (NLD) of HRV, presented in the form of time series, is proposed to obtain visualization of chaotic processes in the body and carry out calculations of the main indicators: estimation of Hausdorff dimension, Hurst's exponent, highest Lyapunov's exponent, sample entropy and approximate entropy. To present the results used Poincaré maps, graphs of the attractor on a small number measurements, singular schedule and trajectories of attractors. Conducting a comparative analysis of the obtained results allows for the development of a complex approach for intelligent data analysis, which can be used to analyze the stability of adaptation processes in the body of operators, the aviation industry, in particular, as one of the triggers for the occurrence of a dangerous event in aviation.

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3 MATERIALS AND METHODS

As the analysis of literary sources proves, the analysis of nonlinear biological processes in the body is based on the presentation of empirical data in the *n*-dimensional space of states. Each of the states characterizes a change in the stability of functioning and the return of its work to a stable state due to biological feedback that characterizes the homeostasis of the organism. The axes in this space are variable states, the description of which changes over time is represented by electrical potentials: electrocardiograms, heart rate variability, electroencephalograms, etc.

The non-stationarity, non-linearity and complexity of the behavior of such data present difficulties in their formalization. Representation of such data as time series allows to evaluate the components of destabilizing factors affecting the stability of the functioning of the biological system. The difficulty in analyzing such time series is that they are traditionally considered as data of a stationary dynamic system, which may have irregular behavior due to its non-linearity. But physiological processes in the body must be considered as non-stationary processes, which necessitates the use of nonlinear dynamics methods for their analysis.

With such an approach, it is advisable to process the biological signal, HRV, in particular, on the basis of time series and divide them into time intervals during which the biological object is in stationary conditions. When using the methods of nonlinear dynamics to process time series, not their representation in the time domain is analyzed, but their vector representation in the phase space. The use of nonlinear dynamics methods allows obtaining additional useful information about the dynamics of biological parameters, which describes the physiological variability of biological processes and allows us to draw a conclusion about the stability of the functioning of this system.

This can be done thanks to the understanding of the complexity of the functioning of the organism, which is associated with the interaction of different subsystems of the organism as separate control circuits that function in a single complex system [15]. Such complexity of the body's structure allows it to be adapted to physiological needs and requirements under the influence of external destabilizing factors [16]. The more complex the phase portrait of the time series, the greater the probability that it may be related to the organism's own variability and its constant adaptation to external factors.

Such complexity of the body's structure allows it to be adapted to physiological needs and requirements under the influence of external destabilizing factors [16]. The more complex the phase portrait of the time series, the greater the probability that it may be related to the organism's own variability and its constant adaptation to external factors [1].

This circumstance leads to the need for a quantitative assessment of the complexity of the dynamics of physiological processes in the body. Such an assessment can be performed using nonlinear dynamics methods using the quantitative assessment of the highest Lyapunov exponent, Hurst exponent, approximate and sample entropy. In connection with the fact that the cardiovascular system performs not only the functions of blood supply to the entire body, and serves as a generally accepted indicator of the stability of the functioning of the entire body, the indicators of which evaluate its adaptive capabilities. Therefore, time series of heart rate variability were chosen in the paper to assess the stability of the body's functioning. These series characterize the duration of RR-intervals in ms. Moreover, these time series were obtained from study participants who do not have clinical symptoms of diseases of the cardiovascular system, which made it possible to use them as a control group for determining the dynamics of chaotic pulsation.

In order to study the spectral nonlinear characteristics of the biomedical signal in the interpolation RR =interpl (time, RR, time, 'spline). That made it possible to project this signal (HRV) onto a uniform time grid with cubic spline interpolation. To study the finite set of HRV points, an attractor was built, which in the phase space allows you to study the phase trajectory of the signal. In the work, a so-called "strange" attractor with a complex geometric structure with a fractal structure was built [17].

To determine the dimension of the "strange" attractor, the Hausdorff dimension estimate was introduced in the work, which determines the dimension of subsets in the metric space:

$$H_D = \lim_{\delta \to 0} \frac{\ln(N(\delta))}{\ln(1/\delta)} .$$

In order to obtain quantitative characteristics of chaotic pulsation by methods of nonlinear dynamics, the highest Lyapunov exponent is calculated in the work, which determines the divergence of two initially close trajectories. To estimate the degree of chaoticity according to the highest Lyapunov exponent, it is necessary to consider two states of the biological system measured at the initial moment of time, and this distance changes over time. If the initial distance is:

$$\left| X_1(0) - X_2(0) \right| = \delta_0 << 1 .$$

The change in distance over time *t* will be equal to:

$$\delta(t) = \left| X_1(t) - X_2(t) \right| .$$

The highest Lyapunov exponent is related to distance $\delta(t)$, by the following dependence:

$$\delta(t) = \delta_0 \exp(\lambda t).$$

Due to the fact that the biological object has chaotic behavior, the highest Lyapunov exponent is $\lambda > 0$.

At the same time, the degree of chaoticity of a biological system can be determined by the highest Lyapunov exponent according to the following principle: the larger the value of λ, the higher the chaoticity, lower values of λ characterize a certain determinism in the movement of such a system and this can be associated with complex

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adaptive transformations in the organism. At the same time, the tendency of the Lyapunov exponent to zero means strict determinism.

While the tendency of λ to 0 characterizes the reduction of chaos in the biological system and the strict definition of the initial conditions of the functioning of the biological object and the definition of the state of the system. Using analytical methods, determining all Lyapunov exponents is quite a difficult task, which is connected with finding a complex analytical solution of a system of differential equations. Therefore, in the work, the authors used a fairly reliable numerical algorithm for estimating the highest Lyapunov exponent based on one implementation of the tracked process based on the speed λ of the distance change between two trajectories over time. Fixation of one reading of the time series $x(t)$ from the realization of all observations x in which all readings of this realization $x(i)$ for which the following condition is fulfilled:

$$\left|x(t)-x(i)\right|<\varepsilon,$$

is the beginnings of ε-near trajectories. Moreover, such readings are considered the beginnings of given trajectories, and the original and neighboring trajectories are formed by sequential recording of readings, starting with t and i, respectively.

In this case, the distance between adjacent trajectories can be defined as:

$$dist(x(t),x(i),\tau)=\left|x(t+\tau)-x(i+\tau)\right|.$$

But this distance has fluctuations, therefore the distance is averaged over all ε-near trajectories and over all counts $x(t)$ of the studied time series. To obtain a stable estimate of the highest Lyapunov exponent, after averaging, S is found, which is equal to:

$$S(\tau)=\frac{1}{N}\sum_{i=1}^{N}\ln\left(\frac{1}{N}\sum_{i=1}^{N_t} dist(x(t),x(i);\tau)\right). \quad (1)$$

Lyapunov exponent characterizes the chaotic pulsation of the studied signal as the degree of exponential divergence of two initially close trajectories.

To quantitatively assess the degree of long-term stability of processes in a biomedical signal, the authors used the Hurst index $H\in[0,1]$ to generalize the random function to the case of the fractal Gaussian function $B_H(t)$:

$$\left\langle \Delta B_H \right\rangle=\left\langle B_H(t)-B_H(t_0)\right\rangle=0.$$

It follows from equation (1) that the variance of increments $S(t\text{–}t_0)$ can be written in the form:

$$S(t-t_0)=\left\langle [B_H(t)-B_H(t_0)]\right\rangle=\sigma^2\left|t-t_0\right|.$$

If then $B_H(t)$ has a Gaussian distribution:

$$P(\Delta \mathrm{B_H} t<\tau)=$$
$$=\frac{1}{\sqrt{2\pi\sigma(t_2-t_1)^H}}\int_{-\infty}^{\tau}\exp(-\frac{1}{2}(\frac{t^2}{\sigma(t_2-t_1)^H})^2)dt.$$

To analyse the parameters of the cardiovascular system, the Hurst method is used [18]. For the existing time series $\xi(t)$, the average value $\left\langle \xi(t)\right\rangle$ on the time interval τ, which has the same dimension as time t, is calculated:

$$\left\langle \xi(\tau)\right\rangle_\tau=\frac{1}{\tau}\sum_{t=1}^{\tau}\xi(\tau).$$

The next stage: calculation of the dependence of the accumulated deviation $X(t,\tau)$ on the time interval (τ);

$$X(t,\tau)=\sum_{u=1}^{\tau}\left\{\xi(u)-\left\langle \xi(t)\right\rangle_\tau\right\}.$$

According to the accumulated deviation, the absolute range function R is calculated:

$$R(\tau)=\max_{1\le t\le\tau}X(t,\tau)-\max_{1\le t\le\tau}X(t,\tau).$$

The range depends on the length of the interval and can increase with its increase. The Hurst method is also referred to as the R/S method because it determines the dependence of the dimensionless function R/S on the length of the time interval τ and is calculated by the standard deviation S of the series $\xi(t)$:

$$s(\tau)=\sqrt{\frac{1}{\tau}\sum_{u=1}^{\tau}\left\{\xi(u)-\left\langle \xi(t)\right\rangle_\tau\right\}^2}.$$

There is an empirical relationship between the normalized swing R/S and the length of the interval τ through the Hurst exponent according to the classical normalized swing method H:

$$\frac{R}{S}=\left(\frac{\tau}{2}\right)^H,$$

H can take on values from 0 to 1.

When $H > 0.5$, the time series has a tendency to increase or decrease, and this is both the predicted trend and the one that was in the past. But $H < 0.5$ characterizes the tendency of the series to change the trend, that is, an increase can change with a decrease, and a decrease with an increase, respectively.

The last stage is the evaluation of the sample entropy and approximate entropy. Approximate Entropy/Sample Entropy (ApEn) is a simple measure of the overall complexity and predictability of time series. ApEn quantifies

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the probability that time series patterns that are close will remain similar for subsequent incremental comparisons. High values of ApEn indicate high irregularity and complexity of the time series data. For healthy people, ApEn values range from about 1.0 to 1.2, for patients after a heart attack, ApEn values are about 1.2 [18]. The improved sample entropy method (SampEn) improves on ApEn and quantifies the conditional probability that two sequences of *m*-consecutive data points that are similar to each other (within a given tolerance *r*) will remain similar if one consecutive point is included [19].

The specified approach allows synthesizing the process of HRV processing by methods of nonlinear dynamics for evaluating the dynamics of information parameter transformation processes.

In the work, calculations of all the described stages were carried out in the MATLAB environment, which allows obtaining quantitative indicators for evaluating heart rate variability according to the following stages: Hausdorff variability, Lyapunov and Hurst indicators, approximation and sample entropy.

The described approach provides an improved assessment of time series and should be a useful tool in studies of the dynamics of the functioning of the cardiovascular system, and due to the comprehensive assessment of several parameters of nonlinear dynamics, they contribute to advanced decision-making regarding the stability of the functioning of the entire organism.

4 EXPERIMENTS

In the work, HRV time series were processed from the database of biomedical signals from the website Phisyonet.org [20]. The time series contained in this database is compiled from long-term time series of healthy volunteers. Holter recordings of participants without clinical symptoms of the disease who did not take medication were used to form this database. In the data of the study participants, the ECG was normal according to the criteria: the minimum nighttime rate is more than 60 beats per minute; night pauses – less than 3 seconds; ventricular extrasystoles – less than 100 in 24 hours, without bursts or polymorphism; supraventricular extrasystoles - less than 100 in 24 hours, without connections; lack of blocks or conduction disturbances. Biological signals were obtained using Holter monitoring by specialized recorders within 24 hours. The recorder data had a reading sampling frequency of 512 and 1024 Hz and a recording sampling frequency of 128 Hz. Signal analyses was performed using Galix and CardioScan software. Time series with artefacts over 8% were not included in the database, and those with artefacts longer than 20 s can be used as a control group to determine the stability of the functioning of the cardiovascular system.

5 RESULTS

To increase the accuracy of biomedical signal processing, it is necessary to remove possible artefacts of various natures. In the work, RR intervals whose duration exceeds the average value by more than two or three standard deviations are considered artefacts. Using the software code in the work, biological signals were cleaned of artefacts. A study of the dependence of the number of removed artefacts on the input parameters of the filter was conducted, the results are presented in Table 1.

Table 1 – Number of removed artifacts for some files

Files name	Parametr of window, *k*	The standard deviation threshold, ns	Number of artefacts, *N*(*a*)
RR002	3	2	503
	5	2	453
	7	2	471
	3	3	207
	5	3	142
	7	3	112
RR003	3	2	618
	5	2	468
	7	2	419
	3	3	447
	5	3	239
	7	3	175

To visualize the process of removing artifacts, Fig. 1 and Fig. 2 show signals R002 and R003 from the database from the website Phisyonet.org and signal data artifacts Examples of the resulting graphs are shown in Fig. 1 and Fig. 2.

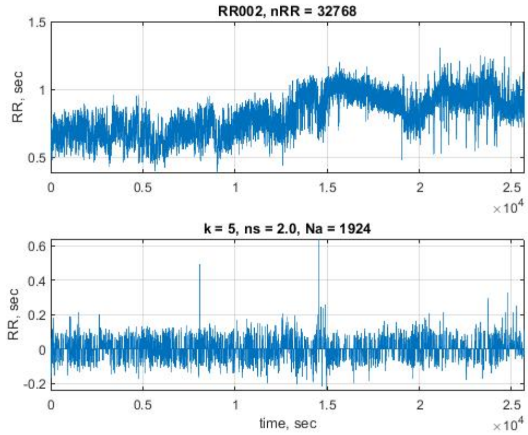

Figure 1 – Graphs of the RR002 signal and its artifacts

In the work, there were “strange” attractors for signals that are being used. Today, a “strange” attractor has acquired a collective meaning, using which the chaotic nature of the system under study is emphasized.

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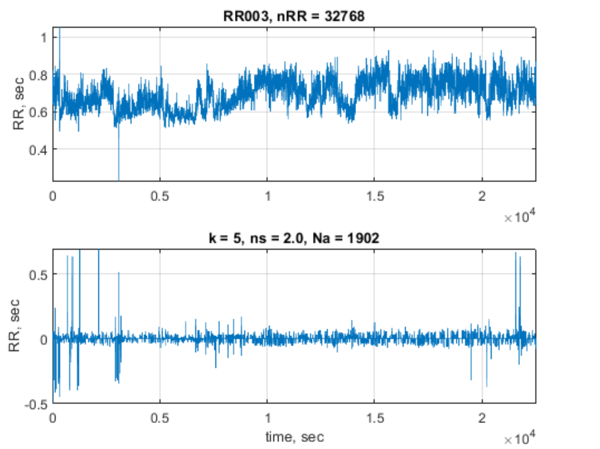

Figure 2 – Graphs of the RR003 signal and its artifacts

According to Takens' theorem [21], the main properties of the attractor will be the same as those of the object under study, and its characteristics can be determined based on the similarity. Graphs of attractors of the studied HRV signals are shown in Fig. 3 and Fig. 4.

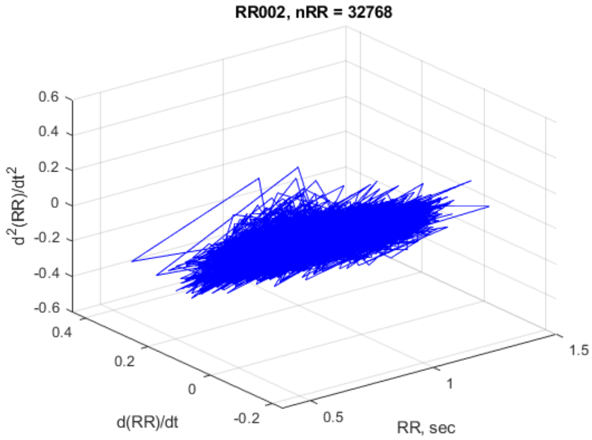

Figure 3 – Attractor of the signal RR002

A strange attractor, unlike a regular attractor, is not a curve or a surface, its geometric structure is very complex, and its structure is fractal. Such attractors are endowed with geometric (scale) invariance. The criteria of a "strange" attractor are trajectory instability in the form of exponential divergence from the attraction zone and fractional dimension. The analysis of the HRV attractor type is an analysis of integral processes based on interactions between individual HRV components or between these components and related characteristics in other organs and systems, occurring as a self-adaptation phenomenon. Three-dimensional histograms of pairs of successive intervals of RR signals were constructed in the MATLAB environment. The results of the obtained histograms in the three-dimensional coordinate space are shown in Fig. 5 and Fig. 6.

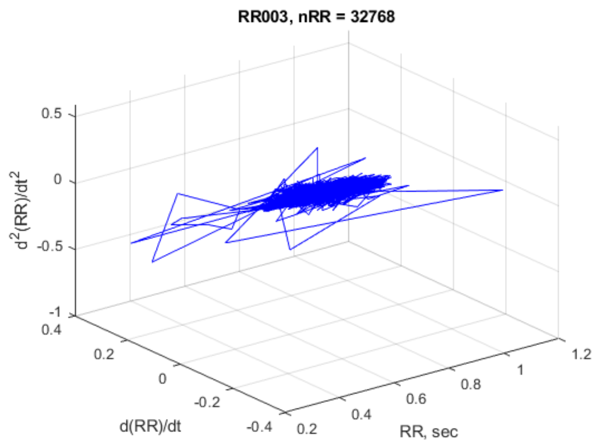

Figure 4 – Attractor of the signal RR003

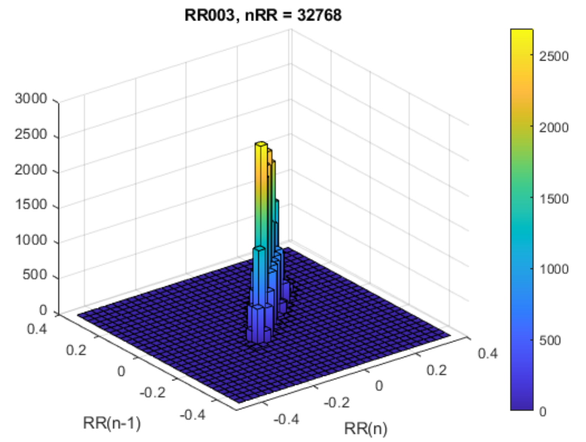

Figure 5 – The three-dimensional histograms RR003 signal

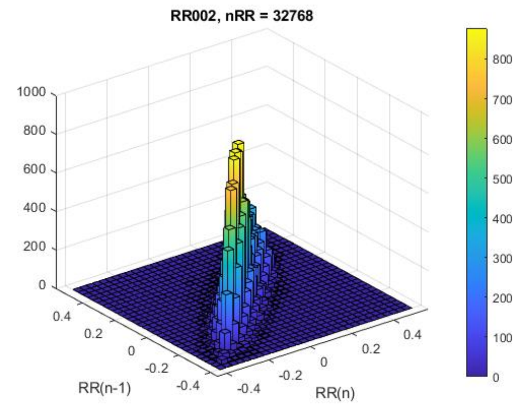

Figure 6 – The three-dimensional histograms RR002. signal

Poincaré maps (graphs) allow you to evaluate the dynamics of the heartbeat based on a simplified embedding of the phase space. Poincaré plot analysis is a quantitative visual technique that classifies the shape of the diagram into functional classes and provides detailed, beat-by-beat information about the heart's behavior. Usually, Poincaré graphs are used for two-dimensional graphic and quantitative representation (scatter diagrams), where the values

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RR(*n*) and RR(*n*+1) are plotted along the axes. Most often, three indices are calculated from Poincaré plots: the standard deviation of the short-term variability of the RR interval (small axis of the cloud, SD1), the standard deviation of the long-term variability of the RR interval (the large axis of the cloud, SD2) and the ratio of the axes (SD1/SD2). For a healthy heart, the Poincaré plot shows a cigar-shaped cloud of points oriented along the line of identity.

These indices are correlated with linear indices. An increased ratio of SD1/SD2 is the most powerful indicator of a disturbance in the stability of the cardiovascular system. Poincaré graphs for the studied HRV signals are shown in the Fig. 7 and Fig. 8.

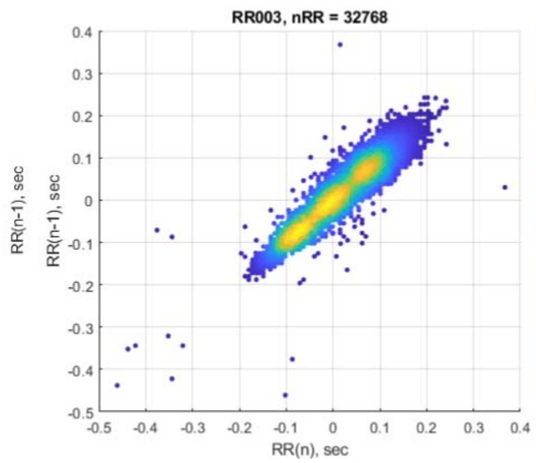

Figure 7 – A Poincaré plot for RR003signal

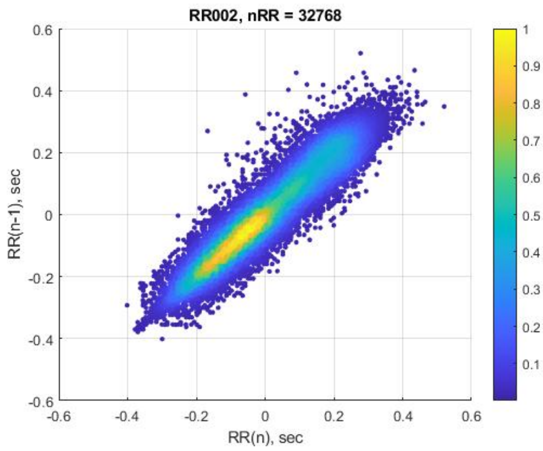

Figure 8 – A Poincaré plot for RR003signal

6 DISCUSSION

As can be seen from Fig. 1 and Fig. 2, real empirical data obtained from biological objects with stochastic influence are difficult to represent and process only by classical standard methods.

Thus, a linear, stationary, time-invariant component can be described using classical frequency and time methods. But non-stationary and non-linear processes that are characteristic of biological systems contain additional information about the chaotic nature and dynamics of changes in the states of this system, requiring the use of non-standard approaches, methods of non-linear dynamics, in particular.

This gave impetus to the search for non-standard approaches to the processing of such empirical data as heart rate variability, which contain information both about the state of the cardiovascular system and about the stability of the functioning of the entire organism.

The importance of reliable processing of empirical data obtained from real biological data is related to the content in these values of an important component that can serve as an indicator of a violation of the functional state of a biological object and plays an important role in forming a decision about the state of the operator as a possible trigger in aviation safety management. Because according to the flight safety risk portfolio, report for the period from 2016 to 2020, of the web portal https://rmd.avia.gov.ua/ cardiovascular diseases are identified as one of the triggers of aviation safety violations. Therefore, the use of nonlinear dynamics methods to obtain additional useful information for assessing the nature of the chaotic nature of processes in the body allows for a visual assessment of the stability of the functioning of the entire system of the operator's body, as a biological system with the stochastic influence of professional destabilizing factors.

Thus, due to the fact that the complex chaotic nature of biological processes describes the constant mechanisms of adaptation of the system to external factors, the RR 002 signal has a visually greater chaoticity than the processes in Fig. 4 and Fig. 5, which can be a sign of healthy adaptation, which is confirmed by the quantitative calculations in Table 2.

Table 2 – The results of the calculation of the main indicators

Signal file	Hausdorff dimension	Highest Lyapunov exponent	Hurst index	ApEn	SaEn
RR002	1.9693	7.6865e-05	0.02608	1.075	0.83034
RR003	1.9727	0.0012	0.21964	0.909	0.68035

The three-dimensional histogram of the studied signals of pairs of consecutive RR intervals in Fig. 6 also confirms the presence of a greater number of chaotic pulsations in the RR 002 signal.

To construct a scatter plot of the RR 002 variable relative to its delay, Poincaré graphs were used to eliminate the limitation of three-dimensional histograms, which consists in the absence of information about the correlation between data points.

The inclusion of the relative frequency of pairs of consecutive data points in the standard Poincaré graph allows you to build a two-dimensional histogram with RR(*n*), RR(*n*+1), having received information about the density of data points (Fig. 7 and Fig. 8 light (yellow) color).

From Fig. 4, it can be seen that the extreme right point is longer by 0.6 s than the nth interval, while the error of determining the RR interval is 8 ms, which may indicate a

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significant imbalance of the body at this moment in time. The same phenomenon can be determined on the Poincaré map of Fig. 7–8, where you can see a significant scatter of individual points at the origin of the coordinates. While for the RR002 signal, there is the presence of repetition of intervals of such a duration that can serve as evidence of the "normality" of such outbreaks for a given organism and serves as evidence of the "normality" of such a situation and a sufficient number of adaptation resources to return to stable functioning, as well as a description of daily variability.

CONCLUSIONS

A component of a comprehensive approach with a defined level of human safety is a timely and reliable assessment of its functional state [22]. The application of human security contributes to a comprehensive response to the multidimensional causes and consequences of the impact of professional destabilizing factors [23].

The scientific novelty of obtained is the fact that for the first time a combination of traditional methods of measurement and processing of biomedical signals in combination with alternative methods for forecasting and diagnosis of biomedical data of individuals, which can be used as a control sample, capable of effectively supplementing the specified methods due to the use of modern methods of signal processing in the time and frequency domains.

The article proposes the use of nonlinear dynamics methods for the analysis of heart rate variability, which allowed a new understanding of heart rate changes in various physiological states, including in the presence of external factors.

The practical significance of obtained results is that the use of the proposed approach provides additional prognostic information and complements the traditional analysis of heart rate variability, since it is the change in the dynamics of heart rate variability that has prognostic value regarding the progression of the impairment of the stability of the functional state of the operator.

Prospects for further research are to study the proposed set of indicators for a broad class of practical problems and use for diagnosis and forecasting in aviation medical.

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ІНТЕЛЕКТУАЛЬНИЙ АНАЛІЗ ЕМПІРІЧНИХ ДАНИХ НА ОСНОВІ ЧАСОВИХ РЯДІВ

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АНОТАЦІЯ

Актуальність. Розглянуто проблему інтелектуального аналізу даних для оцінки стабільності функціонування операторів як складової управління безпекою в авіації. Дослідження присвячене аналізу складності та хаотичності фізіологічних процесів на основі методів нелінійної динаміки. Об'єктом дослідження є процес аналізу варіабельності серцевого ритму методами нелінійної динамік.

Мета роботи – оброблення біомедичних сигналів для оцінювання хаотичності процесів із використанням нелінійних методів. Результати дослідження можуть бути використані під час побудови математичних методів нелінійної динаміки для опису емпіричних даних такого роду. Експериментальні дослідження надають змогу рекомендувати використання методів нелінійної динаміки в якості додаткової незалежної інформації, що дозволяє проаналізувати хаотичну складову біомедичних сигналів для уникнення хибних рішень при професійному відборі та оцінюванні поточного стану операторів авіаційної галузі як одну з причин несприятливих подій в авіації.

Перспективами подальших досліджень може бути створення методології на основі методів нелінійної динаміки, яка дозволить підвищити достовірність прогнозування дисфункції серцево-судинної системи, як індикатора зміни рівноваги функціонального стану оператора на основі додаткових інформативних параметрів, що можуть бути використані для оцінки тригерів несприятливих подій в авіації, а також експериментальне дослідження запропонованих математичних підходів для широкого кола діагностичних задач.

Метод. Проведено аналіз біомедичних даних для отримання додаткової корисної інформації при оцінювання хаотичних процесів для визначення стабільності функціонування біологічної системи при прийнятті рішення про поточний стан оператора. Проведена кількісна оцінка складності фізіологічної динаміки для визначення стійкості процесів управління підсистемами організму та їх постійної адаптації до змін зовнішнього середовища. Наявність значних нелінійностей у біомедичних сигналах пов'язана з появою динамічної складової, яка описує хаотичний характер процесів організму. Завдяки тому, що біомедичні сигнали мають як періодичну, так і хаотичну складову, вивчення останньої дає змогу визначити інформаційну складову характеру внутрішньої організації організму та надати інформацію про можливу дестабілізацію функціонального стану оператора. Використання методів нелінійної динаміки для вивчення змін в організмі оператора та надання додаткової незалежної прогностичної інформації доповнює традиційний аналіз даних у часовій та частотній областях. Запропоновано декілька показників, отриманих методами нелінійної динаміки, що сприяють розширенню діагностичного рішення на основі емпірічних даних.

Результати. Результати дослідження можуть бути використані під час побудови математичних моделей для опису емпіричних даних такого роду.

Висновки. Застосування запропонованого підходу надає додаткову прогностичну інформацію та доповнює традиційний аналіз варіабельності серцевого ритму, оскільки саме зміна динаміки варіабельності серцевого ритму має прогностичне значення щодо прогресування порушення стабільності функціонування стану оператора. Зміни в динаміці варіабельності серцевого ритму мають прогностичне значення щодо прогресування біологічного дисбалансу на основі аналізу функціонування серцево-судинної системи. При застосуванні до окремої біологічної системи протягом певного періоду часу ці показники можуть бути діагностично корисними, диференціюючи прогресування функціональної нестабільності. Крім того, вони можуть бути цінним доповненням до сучасних систем моніторингу людського фактору. Перспективами подальших досліджень може бути створення методології із поєднанням використання класичних методів аналізу даних з додатковим використан-

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ням методів нелінійної динаміки для підтвердження адекватності прийняття рішення про поточний стан оператора за інформативними параметрами, а також експериментальне вивчення запропонованих математичних підходів для широкого кола практичних задач різного характеру та розмірності.

КЛЮЧОВІ СЛОВА: методи нелінійної динаміки, карти Пуанкаре, аттрактор, старший показник Ляпунова, вибіркова ентропія, варіабельності серцевого ритму, стабільність функціонування, оператор.

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